ปรับปรุงการตรวจจับพยาธิสภาพของทรวงอกจากการเอ็กซ์เรย์ทรวงอกด้วยการเรียนรู้เชิงลึก โดยใช้การถ่ายโอนการเรียนรู้และการปรับปรุงภาพ

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บทคัดย่อ

งานวิจัยนี้คำนึงถึงความสำคัญของภาพถ่ายรังสีทรวงอกซึ่งจำเป็นสำหรับแพทย์ในการระบุและติดตามโรคเกี่ยวกับปอด เนื่องด้วยปริมาณรังสีแพทย์ที่มีความชำนาญในการระบุโรคในภาพเอ็กซเรย์ทรวงอกนั้นยังคงขาดแคลน ดังนั้นนักวิจัยจึงพัฒนาโมเดลการเรียนรู้เชิงลึกเพื่อลดปัญหานี้ และ CheXNet เป็นหนึ่งในโมเดลล้ำสมัยที่สามารถตรวจจับโรคปอดได้ 14 โรค งานวิจัยนี้จึงใช้เทคนิคการปรับปรุงภาพ 6 เทคนิคกับภาพเอ็กซเรย์ก่อนใช้งานร่วมกับ ChexNet เพื่อปรับปรุงประสิทธิภาพการตรวจจับ เทคนิคทั้งหกประกอบด้วย Gamma, Complement, HE, CLAHE, BCET และ MMCS ในการศึกษานี้แบ่งออกเป็นสองแบบคือ ศึกษาประสิทธิผลของการใช้เทคนิคการปรับปรุงแบบเดียว (single channel) และการรวมเทคนิคเหล่านี้เข้ากับภาพต้นฉบับ (multi-channel) Gamma เป็นเทคนิคที่ช่วยในการปรับปรุงการตรวจหาที่สูงที่สุดและเสถียรที่สุดโดยใช้เทคนิคนี้เพียงอย่างเดียว สามารถเพิ่มประสิทธิภาพได้ที่ 0.628% AUCROC ใน 14 โรค และการรวมภาพต้นฉบับกับภาพที่ปรับปรุงด้วย Gamma เทคนิคร่วมกับภาพที่ปรับปรุงด้วย CLAHE สามารถเพิ่มประสิทธิภาพสูงขึ้น 0.7% AUCROC สำหรับทั้ง 14 โรค นอกจากนั้นการรวมกันของทั้งสามารถนี้สามารถตรวจจับโรคปอดบวมได้ดีขึ้นอย่างเห็นได้ชัดโดยมากกว่า CheXNet ถึง 2%

คำสำคัญ : CheXNet, Chest x-ray, image enhancement, multichannel input image, DenseNet

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IMPROVING CHEST PATHOLOGIES DETECTION FROM CHEST X-RAY WITH DEEP LEARNING USING TRANSFER LEARNING AND IMAGE ENHANCEMENT

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Abstract

This research is concerned with chest radiography, which is essential for doctors to determine and follow up on lung disease. However, practicing radiologists have an insufficient ability to identify diseases in chest x-ray images. Therefore, the researchers developed deep-learning models to mitigate this problem, and CheXNet is one of the state-of-the-art models that can detect 14 lung pathologies. This research applied six image enhancement techniques to the x-ray images before using ChexNet to improve detection performance. The six techniques consisted of Gamma, Complement, HE, CLAHE, BCET, and MMCS. In addition, we studied the effectiveness of using a single enhancement technique (single channel) and a combination of them to the original image (multi-channel). Gamma gave the highest and most stable detection improvement using a single enhancement technique at 0.628% AUCROC in 14 diseases. Combining the original image, Gamma-enhanced image, and CLAHE-enhanced image shows 0.7% AUCROC improvement for 14 diseases. Moreover, this combination offers outstanding Pneumonia detection, which is 2% more than CheXNet.

Keywords: CheXNet, Chest x-ray, image enhancement, multichannel input image, DenseNet

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INTRODUCTION

Medical imaging aids technology can support radiologists in making quicker and even more accurate diagnoses by providing a visual image of the inside of the human body. As a result, the doctor can treat diseases more effectively, resulting in better patient care. Medical imaging has progressed in measuring speed, spatial resolution, and contrast. Having this helpful tool necessitates having enough capacity to have qualified radiologists evaluate the required data.

Medical X-rays are images that diagnose several of the most sensitive human body organs, such as the bones, chest, teeth, and head. For generations, medical professionals have utilized this approach to investigate and visualize fractures or anomalies in specific body areas. Since X-rays are excellent diagnostic instruments for chest illnesses, they are non-invasive and cost-efficient. X-rays can reveal pathological changes, cavitations, consolidations, infiltrates, blunted costophrenic angles, and small, widely scattered nodules can all be seen on CXR images. Pleurisy, effusion, pneumonia, bronchitis, infiltration, nodule, atelectasis, pericarditis, Cardiomegaly, Pneumothorax, fractures, and many more disorders and diseases can be diagnosed with a chest X-ray[1].

Chest pathologies interpreted from chest X-rays require an expert radiologist. The improvement of time consumption and accuracy of interpreting is required to mitigate the shortage of expert radiologists. Recently, deep learning (with Convolution Neuron Network: CNN) has been successful in medical mage interpreting. Implementing Transfer learning and Image enhancement techniques would improve the performance deep learning model.

The existing deep learning model, CheXNet[2], for diagnosing 14 chest pathologies performs well on most of them. However, some pathology still required improvement, e.g., Infiltration, Nodule, Pneumonia, and Consolidation. This experiment will focus on improving the model performance using three image enhancement techniques. Then, Transfer learning and finetune the model with a new form of chest X-ray from Image enhancement techniques].

METHODOLOGY

STEP 1: Dataset

The whole corpus of ChestX-ray1 4 is used to train and evaluate techniques for multilabel pathology classification. Figure 8 shows 8 chosen ChestX-ray14 samples. The collection includes 112,120 frontal chest X-rays from 30,805 patients.

In this research, they randomly split the dataset into training (28744 patients, 98637 images), validation (1672 patients, 6351 images), and test (389 patients, 420 images). There is no patient overlap between the sets.

The collection only includes preprocessed images and does not include the raw DICOM images. [3] used the encoded display settings to conduct a simple preprocessing while the pixel depth was decreased to 8 bits. Also, each image was resized to 1024 x1024 pixels without concern for the aspect ratio.

STEP 2: Analyse the dataset

The distribution of each class and statistics for non-image data. The prevalence of each pathology was usually rare, with frequency ranging from 0.2 percent to 17.74 percent. The patient gender and view position distributions were relatively equal, with ratios of 1.3 and 1.5, respectively. The distribution of patient age in ChestX-ray14. The average age of the patients was 46.87 years, with a standard deviation of 16.60.

More exploration into the dataset. As per Figure 10, check each CXR image, how many pathologies will show per image, and visualize the bar chart. Evident exist found some insight information on each disease that have some correlation.

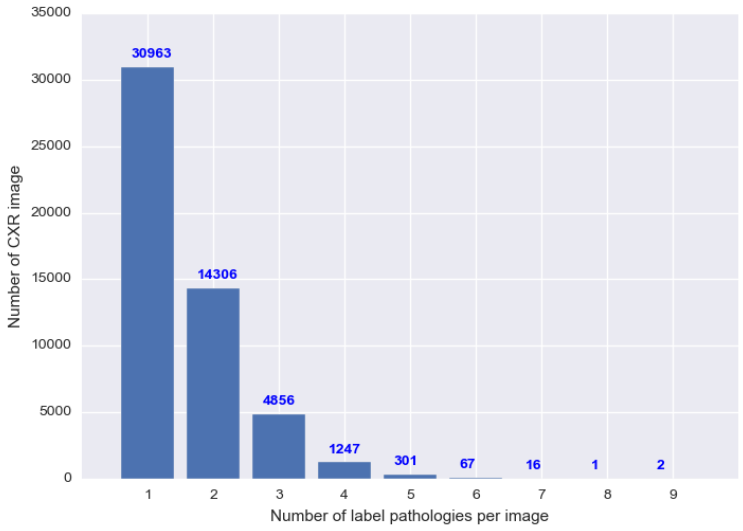

Figure 10: Explore the Number of labels per one image distribution without “No Finding” included

STEP 3: Flow of work

In This study, six types of Image enhancement are implemented from the flowchart. To experiment with preprocessing on each Chest X-ray image of each 14 diseases.

Figure 1 1 shows frontal-view chest X-ray images are put through the image enhancement process. Prepared datasets were separated on each processed image from each technique to prepare for training the Transfer Learning CheXNet model.

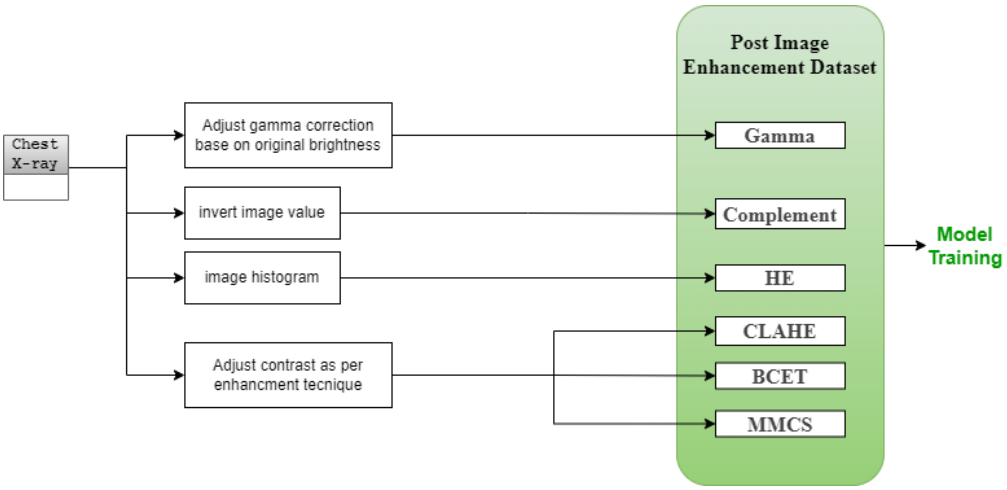

Figure 1: Flowchart of a subprocess for post Image Enhancement dataset

The proposed work is shown In Figure 14. Initially, the test dataset of chest X-ray images will go through the Deep CNN pertained model, the “CheXNet” model. The result is used for the baseline in performance compared with the result from different image enhancement techniques on CheXNet fine-tune model.

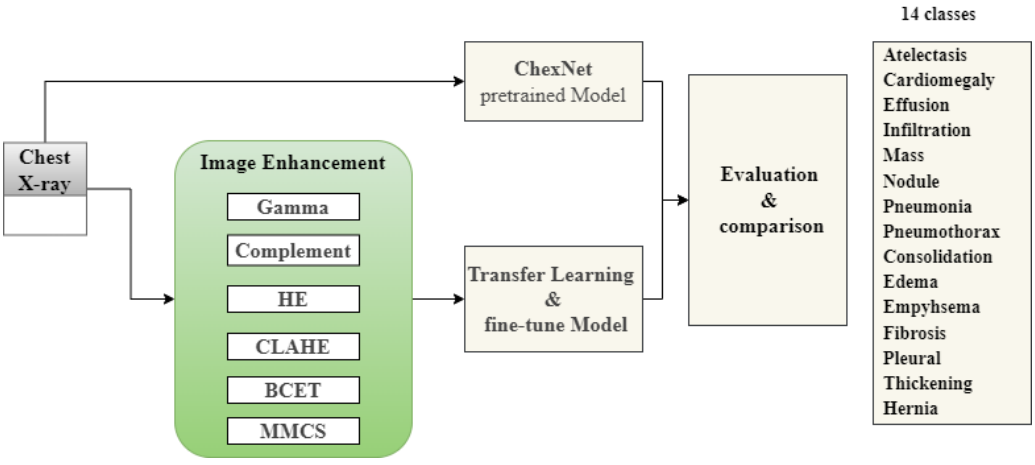

Figure 2: Flow of the Methodology for Single Channel Image Enhancement

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STEP 4: Training Procedure

We train chest X-ray classification models with pretrained ImageNet and use the weight obtained from our training condition without CheXNet weight. The task of interest is to predict the probability of different pathologies from chest X-rays. We use the 112,120 frontal chest X-rays from 30,805 patients labeled for the presence or absence of 14 radiological observations, split the dataset into training (28744 patients, 98637 images), validation (1672 patients, 6351 images), and test (389 patients, 420 images). There is no patient overlap between the sets. The base model used is DensNet121, ImageNet weight loaded, batch size 32, and the initial learning rate is 0.001. The image dimension input 224x224 from Chest X-ray image 1024x1024, used callback "ReduceLROnPlateau" to decay the learning rate each epoch, and the minimum learning rate is 1e-8, optimizer "Adam" with standard parameters (β1 = 0.9 and β2 = 0.999), loss function "binary_crossentropy" and train 50 epochs. Imbalance data optimization by class weighting. An activation function is Sigmoid. Data Augmentation was implemented by flipping the image horizontally only to alter between the PA and AP types of the Chest X-ray image. The best weight from training with an original image of the Chest X-ray 14 dataset is CheXNet weight. Moreover, the models were trained on Nvidia GeForce RTX 3080 GPUs with 23 GB of memory.

STEP 5: Evaluation and Comparison

We evaluate models using the average of their AUROC metrics (AUC) on the 14 radiological observations (Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, Hernia) and Comparison between image enhancement technique. The ROC curve is plotted with TPR against the FPR where TPR is on the y-axis and FPR is on the x-axis.

Defining terms used in AUC and ROC Curve

$$TPR\ or\ recall\ or\ Sensitivity\ = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$FDR = 1 - Specificity = \frac{FP}{TN + FP}$$

AUC measures the volume that the ROC curve is generating by computing the sensitivity and 1-specificity by evaluating all possible threshold values. The greater this area, the better the algorithm tends to be. The axis of a ROC plot consists of the false positive rate (1- specificity, FPR) against the true positive rate (sensitivity, TPR). An excellent model has an AUC near one, meaning it has a good separability measure. A poor model has an AUC near 0, meaning it has the worst separability measure. It means it is reciprocating the result. It predicts 0s as 1s and 1s as 0s.

AUC - ROC curve is a performance measurement for classification problems at various threshold settings. ROC is a probability curve, and AUC represents the degree or measure of separability. It tells how much the model is capable of distinguishing between classes. The higher the AUC, the better the model predicts 0 classes as 0 and 1 classes as 1. By analogy, the Higher the AUC, the better the model is at distinguishing between patients with the disease and no disease. Furthermore, when AUC is 0.5, the model has no class separation capacity.

Pretrained with CheXNet Table 4 below shows the result of CheXNet Pretrained from paper and "Our_weight" training from scratch on DenseNets with ImageNet weight use for the based line on this study. The result is slightly different from the CheXNet paper due to the python dependencies environment and configurations that affect the training process.

RESULTS AND DISCUSSION

In the single channel image enhancement experiment, each image enhancement technique was fed to train five times to confirm the trend and performance is not occasionally result. The result table below compares AUROC from each image enhancement technique and the AUROC from the original image model with the weight train by ourselves with reference AUROC from the previous research paper of CheXNet[2].

Single Channel Image Enhancement Result comparison

We observe pathologies improve differently depending on each image enhancement technique. Based on the selection of the best mean AUROC from each Single Channel image enhancement model training, the comparison result is shown in table 11. The best overall can use mean AUROC to indicate from the table; MMCS and Gamma correction is the best overall performance on 14 pathologies from these single channel input training experiments. For the pathology example of a Nodule alone, the CLAHE is the best technique to improve disease detection by 3.37 percent. The second best for Nodule detection is the Min Max Contrast Stretching technique, as shown in Table 11.

									Percent Increment					
Pathology	Paper	myW	mmcs5	gam5	invert4	clahe3	he1	bcet5	mmcs5	gam5	invert4	clahe3	he1	bcet5
Atelectasis	0.8094	0.810745	0.8121	0.8103	0.8104	0.8100	0.8090	0.8045	0.1732	-0.0545	-0.0414	-0.0884	-0.2112	-0.7758
Cardiomegaly	0.9248	0.891407	0.8987	0.8904	0.8999	0.8966	0.8975	0.8828	0.8174	-0.1129	0.9558	0.5820	0.6875	-0.9663
Effusion	0.8638	0.877551	0.8786	0.8801	0.8810	0.8787	0.8759	0.8723	0.1185	0.2881	0.3952	0.1366	-0.1851	-0.6001
Infiltration	0.7345	0.715202	0.7172	0.7138	0.7148	0.7152	0.7148	0.7097	0.2730	-0.1956	-0.0493	0.0019	-0.0581	-0.7627
Mass	0.8676	0.845511	0.8459	0.8479	0.8494	0.8393	0.8494	0.8349	0.0510	0.2829	0.4579	-0.7397	0.4600	-1.2547
Nodule	0.7802	0.714531	0.7379	0.7361	0.7334	0.7482	0.7349	0.7379	3.2709	3.0228	2.6356	4.7177	2.8451	3.2673
Pneumonia	0.768	0.772134	0.7809	0.7877	0.7842	0.7791	0.7730	0.7826	1.1332	2.0143	1.5655	0.9039	0.1176	1.3501
Pneumothorax	0.887	0.87609	0.8753	0.8793	0.8755	0.8742	0.8739	0.8604	-0.0936	0.3691	-0.0715	-0.2141	-0.2514	-1.7951
Consolidation	0.7901	0.798645	0.8007	0.8016	0.7954	0.7983	0.7981	0.7940	0.2550	0.3745	-0.4001	-0.0417	-0.0667	-0.5775
Edema	0.8878	0.887843	0.8853	0.8877	0.8881	0.8806	0.8832	0.8787	-0.2839	-0.0124	0.0294	-0.8214	-0.5280	-1.0295
Emphysema	0.9371	0.896654	0.9047	0.9012	0.9024	0.9068	0.8931	0.8878	0.8987	0.5066	0.6455	1.1344	-0.3941	-0.9902
Fibrosis	0.8047	0.757111	0.7582	0.7634	0.7588	0.7616	0.7589	0.7600	0.1405	0.8337	0.2205	0.5929	0.2302	0.3847
Pleural_Thickening	0.8062	0.78352	0.7823	0.7912	0.7845	0.7861	0.7928	0.7896	-0.1495	0.9825	0.1263	0.3350	1.1825	0.7802
Hernia	0.9164	0.872689	0.8959	0.8810	0.8770	0.8796	0.8695	0.9031	2.6588	0.9535	0.4931	0.7928	-0.3686	3.4842
mean auroc	0.8413	0.8214	0.8267	0.8266	0.8254	0.8253	0.8231	0.8213	0.6442	0.6280	0.4807	0.4767	0.2116	-0.0121

Table 11: AUROC comparison from Transfer Learning and fine-tuning with six image enhancement techniques and the AUROC from the original image base on the best overall AUROC (mean AUROC).

Moreover, The BCET and Gamma correction improve Hernia detection. However, The Balance Contrast Enhancement Technique decreases the performance of the remaining pathology except for Nodule and Hernia. The best improvement in Pneumonia detection used Gamma correction.

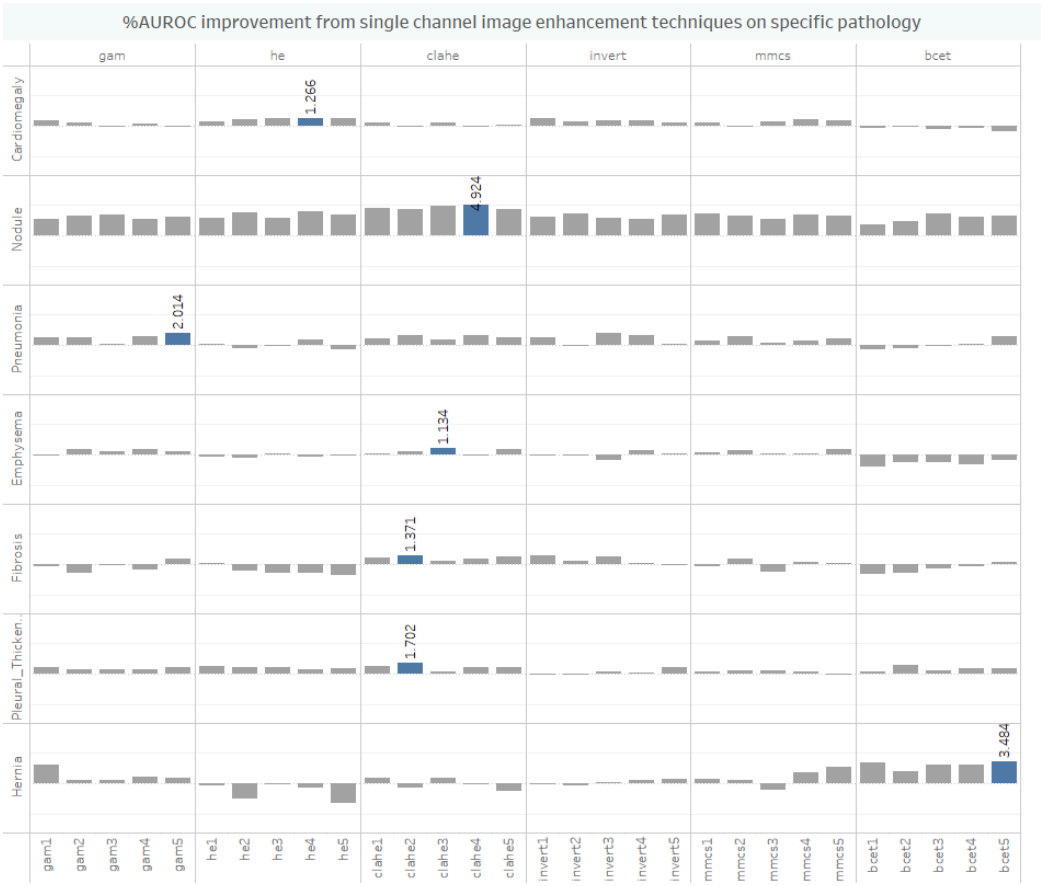

Figure 3: The percentage of AUROC improvement from single image enhancement techniques on the specific pathology

Each pathology detection base on each image enhancement technique, from figure 18, shows the potential performance for the specific uses for one class of pathology detection. When observing different perspectives from all the experiments on image enhancement techniques specific to the disease, the disease which significantly improves is Cardiomegaly, Nodule, Pneumonia, Emphysema, Fibrosis, Pleural Thickening, and Hernia. Cardiomegaly specifically chooses the Histogram Equalization technique to maximize improvement from these experiments. Nodule Fibrosis Emphysema and Pleural Thickening chose the Contrast limited adaptive

histogram equalization; Pneumonia used the Gamma correction technique, and Hernia chose the Balance Contrast Enhancement Technique. The best weight trained from the experiment is shown in Figure 18, according to each pathology

CONCLUSION

Single Channel image enhancement can improve lung disease detection performance from X-ray images overall and specific pathology. For detecting 14 pathologies from 6 image enhancement techniques, MMCS, Gamma Correction, and CLAHE are the top 3 practical improvements. CLAHE is an upgraded version of Histogram Equalization. Min Max Linear Contrast Stretching (MMCS). Contrast enhancement is more suitable for these pathologies on this experiment than Balance Contrast Enhancement Technique (BCET). From the result in Single Channel image enhancement, we compare and observe the performance with AUROC in figure 18.

Based on this experiment, BCET is best for the specific improved detection of Hernia for practical use in specific pathology. Gamma correction is best for specific improved detection of Pneumonia.

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